

1 Fraud

Charlie's Angels

2024-05-18

```
knitr::opts_chunk$set(warning = FALSE, message = FALSE)
```

Libraries to be used:

```
library(readr)
library(tidyr)
library(dplyr)
library(lubridate)
library(ggplot2)
library(magrittr)
library(data.table)
```

A. Importing Fraud Data

```
read_fraud <- function(folder = getwd()) {
  files <- list.files(path = folder, pattern = "*.csv", full.names = TRUE)
  transactions_list <- lapply(files, read)
  transactions <- bind_rows(transactions_list)
  transactions <- transactions %>%
    mutate(
      CardType = as.factor(CardType),
      Fraud = as.factor(Fraud)) %>%
    select(TimeStamp, CardType, Amount, Fraud)
  return(transactions)
}
```

#Input your directory here (to verify)

```
transactions <- read_fraud("C:/Users/amore_6ou078y/OneDrive/Documents/UP Subjects/Stat 125/R/Fraud Data")
head(transactions)
```

##	TimeStamp	CardType	Amount	Fraud
##	<POSct>	<fctr>	<num>	<fctr>
## 1:	2023-01-01 00:00:05	Dr	640.28	No
## 2:	2023-01-01 00:00:18	Cr	1500.00	Yes
## 3:	2023-01-01 00:00:25	Cr	3821.77	No
## 4:	2023-01-01 00:00:44	Cr	4849.85	No
## 5:	2023-01-01 00:00:47	Dr	1500.00	Yes
## 6:	2023-01-01 00:00:57	Dr	220.19	No

B. Single Line Codes

```
loss_tally <- filter(.data = transactions, Fraud == "Yes") %>% summarise(Sum = sum(Amount))
loss_tally
```

```
##           Sum
## 1 39465197
```

1. For the whole year of 2023, how much did the bank lose due to fraud transactions?

- 39,465,197 pesos lost due to fraud transactions.

```
date_transactions <- filter(.data = transactions, Fraud == "Yes") %>%
  mutate(Date = as.Date(TimeStamp)) %>%
  group_by(Date, Fraud) %>%
  summarise("number" = n(), .groups = 'drop') %>%
  arrange(desc(number))

head(date_transactions, 4)
```

```
## # A tibble: 4 x 3
##   Date      Fraud number
##   <date>    <fct>  <int>
## 1 2023-12-24 Yes      336
## 2 2023-12-31 Yes      333
## 3 2023-12-25 Yes      323
## 4 2023-01-01 Yes      219
```

2. Find the top 4 days with the greatest number of fraudulent transactions.

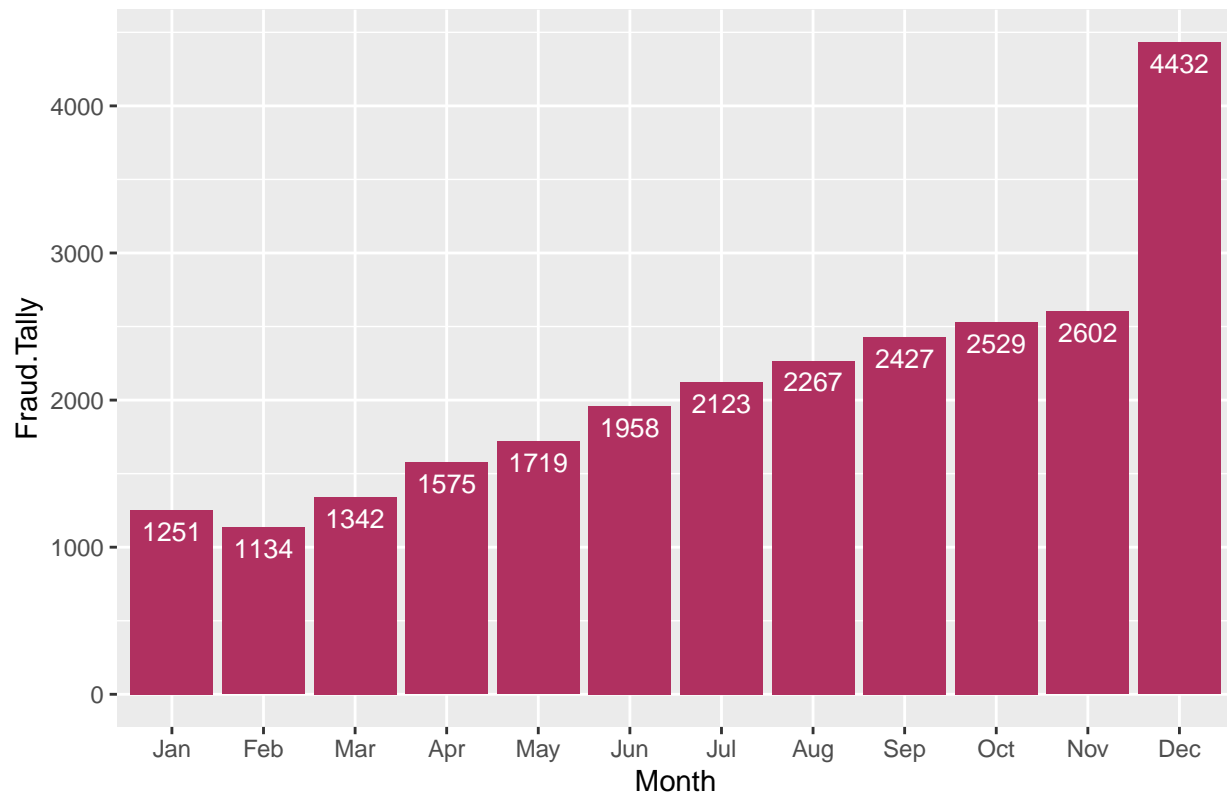
1. December 24, 2023 (336)
2. December 31, 2023 (333)
3. December 25, 2023 (323)
4. January 1, 2023 (219)

3. Create a bar chart showing number of fraud transactions per month.

```
by_month <- mutate(date_transactions, Month = lubridate::month(Date, label = TRUE)) %>%
  group_by(Month) %>%
  summarise("Fraud.Tally" = sum(number)) %>%
  ggplot(aes(x = Month, y = Fraud.Tally)) +
  geom_bar(stat="identity", fill = 'maroon') +
  geom_text(aes(label=Fraud.Tally), vjust=1.6, color="white", size=3.5) +
  ggtitle("Number of Fraud Transactions per Month")

by_month
```

Number of Fraud Transactions per Month



```
by_CardType <- select(transactions, CardType, Fraud) %>%
  mutate(value = ifelse(Fraud == "Yes", 1, 0)) %>%
  group_by(CardType) %>%
  summarise("number" = n(), tally = sum(value)) %>%
  mutate("P(fraud|CardType)" = tally/number)
```

by_CardType

```
## # A tibble: 2 x 4
##   CardType number tally 'P(fraud|CardType)'
##   <fct>      <int> <dbl>          <dbl>
## 1 Cr       1622845  1966          0.00121
## 2 Dr       3785633 23393          0.00618
```

4. Which type of card is less prone to fraud: credit or debit cards?

- $P(\text{fraud} | \text{Credit}) = 0.001211453$
- $P(\text{fraud} | \text{Debit}) = 0.006179416$

Thus, **Credit cards are less prone to fraud**, since relative frequency of fraud in Credit cards is lower than in Debit cards.